Video: Tracking and Action Recognition

EECS 442 – David Fouhey

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http://web.eecs.umich.edu/~fouhey/teaching/EECS442_F19/

Today: Tracking Objects

- Goal: Locating a moving object/part across video frames
- This class:
  - Examples
  - Probabilistic Tracking
  - Kalman filter
  - Particle filter

Slide credit: D. Hoiem

Tracking Examples

Video credit: B. Babenko

Tracking Examples

Best Tracking

Slide credit: B. Babenko

Difficulties

- Erratic movements, rapid motion
- Occlusion
- Surrounding similar objects

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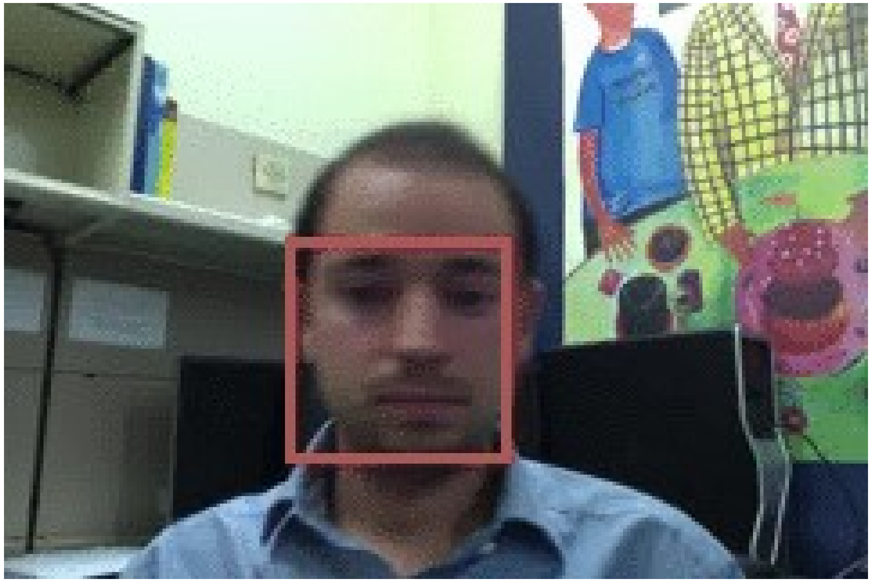
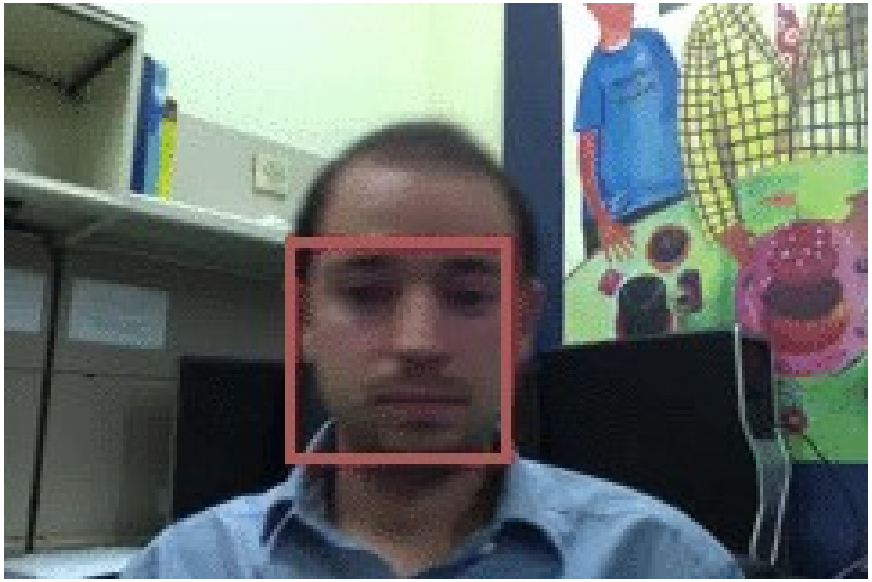


Tracking by Detection

Tracking by detection:

- Works if object is detectable
- Need some way to link up detections



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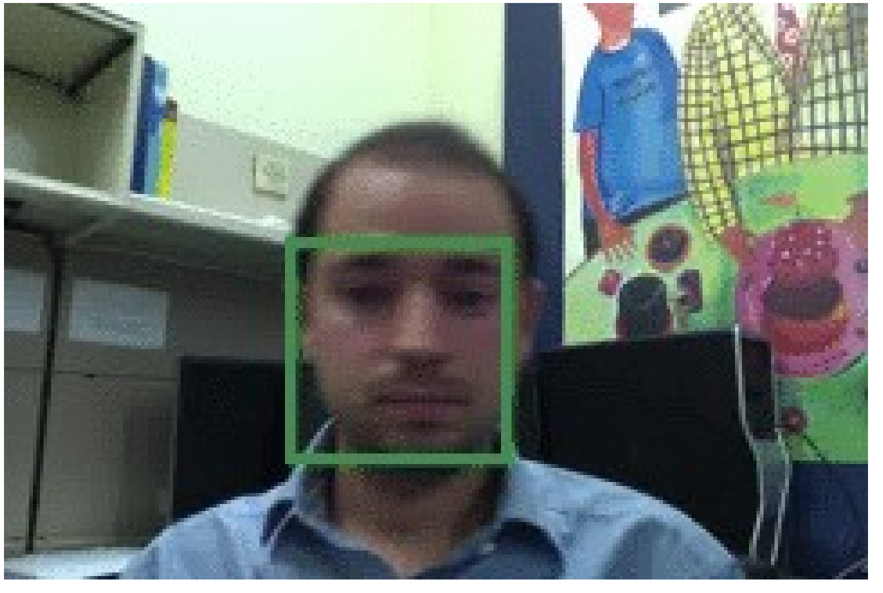
Tracking With Dynamics

Based on motion, predict object location

- Restrict search for object
- Measurement noise is reduced by smoothness
- Robustness to missing or weak observations



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Strategies For Tracking

- Tracking with motion prediction:
  - Predict object's state in next frame.
  - Fuse with observation.

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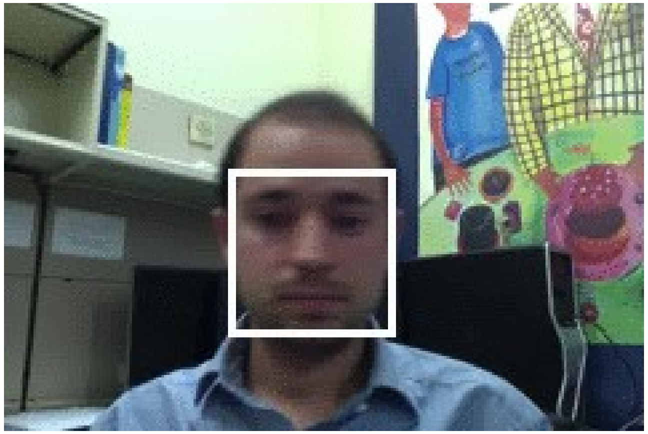
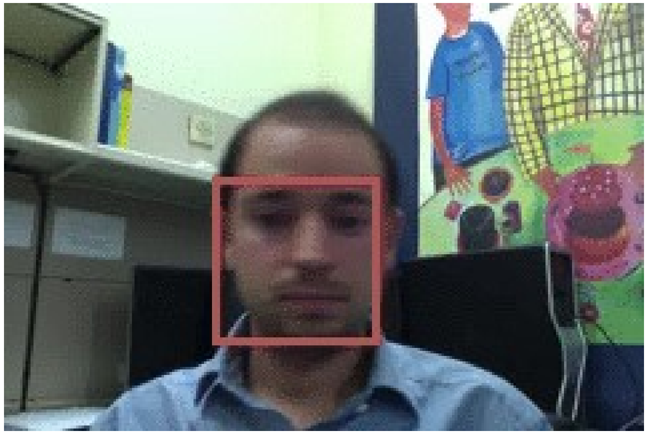
General Tracking Model

State X: actual state of object that we want to estimate. Could be: Pose, viewpoint, velocity, acceleration.



Observation Y: our "measurement" of state X. Can be noisy. At each time step t, state changes to X_t, get Y_t.



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Steps of Tracking

Prediction: What's the next state of the object given past measurements

$$P(X_t | Y_0 = y_0, \ldots, Y_{t-1} = y_{t-1})$$

Correction: Compute updated estimate of the state from prediction and measurements

$$P(X_t | Y_0 = y_0, \ldots, Y_{t-1} = y_{t-1}, Y_t = y_t)$$

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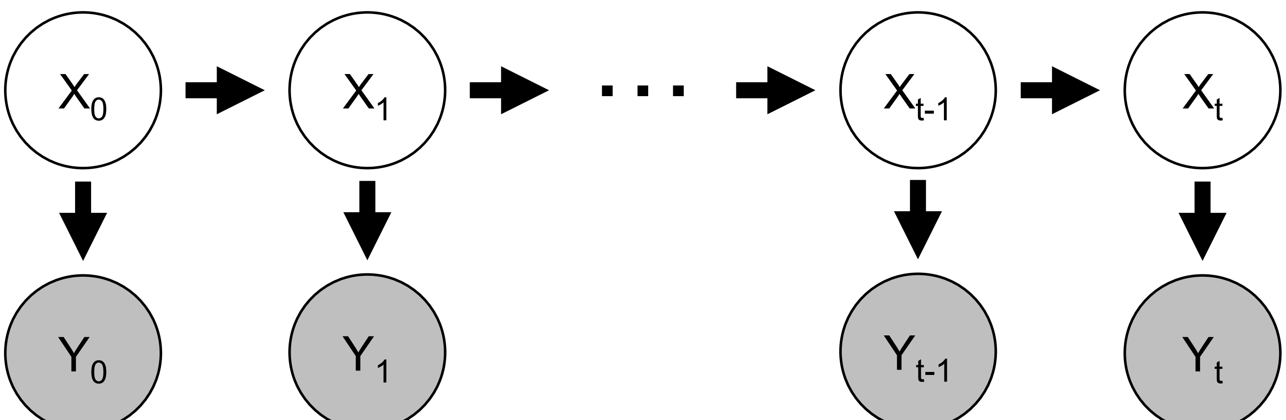
Simplifying Assumptions

Only immediate past matters (Markovian)

$$P(X_t | X_0, \ldots, X_{t-1}) = P(X_t | X_{t-1})$$

Measurement depends only on current state (Independence)

$$P(Y_t | X_0, Y_0, \ldots, X_{t-1}, Y_{t-1}, X_t) = P(Y_t | X_t)$$



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Problem Statement

Have models for:

(1) P(next state) given current state / *Transition*

$$P(X_t|X_{t-1})$$

(2) P(observation) given state / *Observation*

$$P(Y_t|X_t)$$

Want to recover, for each timestep t

$$P(X_t|y_0, \ldots, y_t)$$

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Probabilistic tracking

- Base case:
  - Start with initial ***prediction***/prior: $P(X_0)$
  - For the first frame, ***correct*** this given the first measurement: $Y_0 = y_0$

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Probabilistic tracking

- Base case:
  - Start with initial ***prediction***/prior: $P(X_0)$
  - For the first frame, ***correct*** this given the first measurement: $Y_0 = y_0$

- Each subsequent step:
  - ***Predict*** X_t given past evidence
  - Observe y_t: ***correct*** X_t given current evidence

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Prediction

Given $P(X_{t-1}|y_0,\ldots,y_{t-1})$ *want* $P(X_t|y_0,\ldots,y_{t-1})$

$$P(X_t|y_0,\ldots,y_{t-1})$$

$$= \int P(X_t, X_{t-1}|y_0,\ldots,y_{t-1})\, dX_{t-1}$$

Total probability

$$= \int P(X_t, |X_{t-1}, y_0,\ldots,y_{t-1}) P(X_{t-1}|y_0,\ldots,y_{t-1})\, dX_{t-1}$$

Condition on X_{t-1}

$$= \int \underbrace{P(X_t, |X_{t-1}\ )}_{\text{dynamics model}} \underbrace{P(X_{t-1}|y_0,\ldots,y_{t-1})\, dX_{t-1}}_{\text{corrected estimate from previous step}}$$

Markovian

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Correction

Given $P(X_t|y_0,\ldots,y_{t-1})$ want $P(X_t|y_0,\ldots,y_{t-1},y_t)$

$$P(X_t|y_0,\dots,y_t)$$

$$= \frac{P(y_t|X_t,y_0,\dots,y_{t-1})P(X_t|y_0,\dots,y_{t-1})}{P(y_t|y_0,\dots,y_{t-1})}$$

Bayes Rule

$$= \frac{P(y_t|X_t)P(X_t|y_0,\dots,y_{t-1})}{P(y_t|y_0,\dots,y_{t-1})}$$

Independence Assumption

$$= \frac{P(y_t|X_t)P(X_t|y_0,\dots,y_{t-1})}{\int P(y_t|X_t)P(X_t|y_0,\dots,y_{t-1})\,dX_t}$$

Condition on X_t

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Correction

Given $P(X_t|y_0,\ldots,y_{t-1})$ want $P(X_t|y_0,\ldots,y_{t-1},y_t)$

$$P(X_t|y_0,\ldots,y_t)$$

observation model

Predicted estimate

$$= \frac{\ldots, y_{t-1})P(X \ldots {}_1)}{\ldots y_t|y_0,\ldots,y \ldots}$$

Bayes Rule

$$= \frac{P(y_t|X_t)P(X_t|y_0,\ldots,y_{t-1})}{P(y_t|y_0,\ldots,y_{t-1})}$$

Independence Assumption

$$= \frac{\boldsymbol{P(y_t|X_t)}P(X_t|y_0,\ldots,y_{t-1})}{\int P(y_t|X_t)P(X_t|y_0,\ldots,y_{t-1})\,dX_t}$$

Condition on X_t

Normalization Factor

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Summarize

Transition — **P(state given past)**

Observation — **P(state given past+present)**

Prediction:

$$P(X_t|y_0,\dots,y_{t-1}) = \int P(X_t, |X_{t-1})P(X_{t-1}|y_0,\dots,y_{t-1})\, dX_{t-1}$$

Correction:

$$P(X_t|y_0,\dots,y_t) = \frac{P(y_t|X_t)P(X_t|y_0,\dots,y_{t-1})}{\int P(y_t|X_t)P(X_t|y_0,\dots,y_{t-1})\, dX_t}$$

Nasty integrals! Also these are probability distributions

Solution 1 – Kalman Filter

- **What's the product of two Gaussians?**
- Gaussian
- **What do you need to keep track of for a multivariate Gaussian?**
- Mean, Covariance

Kalman filter: assume everything's Gaussian

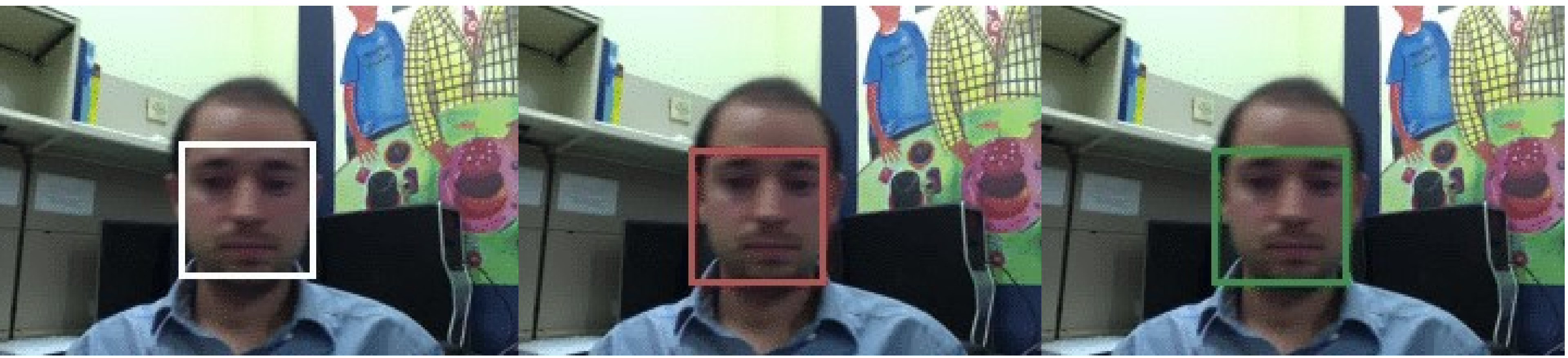
Solution 1 – Kalman Filter

“The Apollo computer used 2k of magnetic core RAM and 36k wire rope [...]. The CPU was built from ICs [...]. Clock speed was under 100 kHz”

Rudolf Kalman

Photo, Quote credit: Wikipedia

Comparison



Ground Truth Observation Correction

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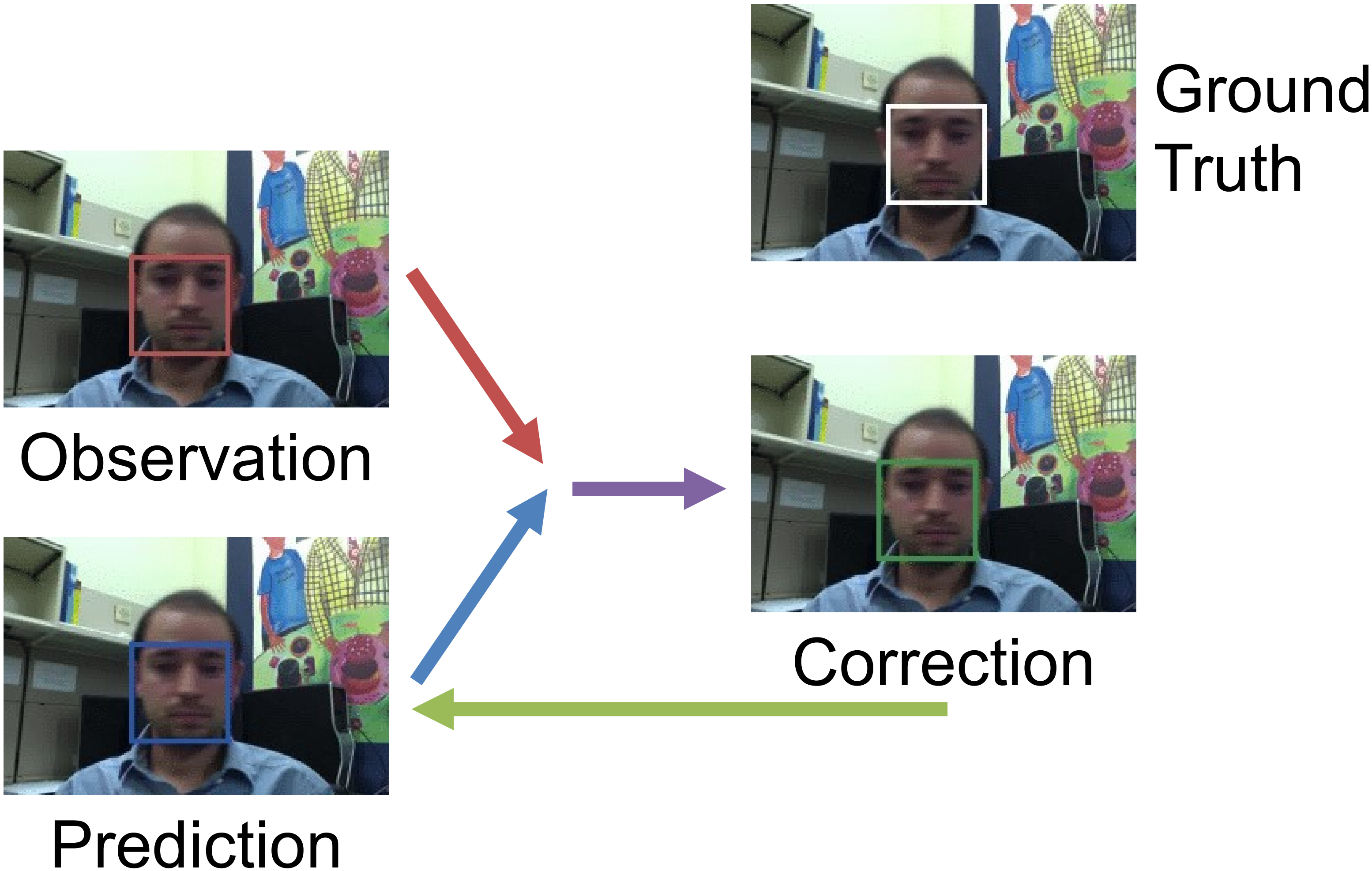
Example: Kalman Filter



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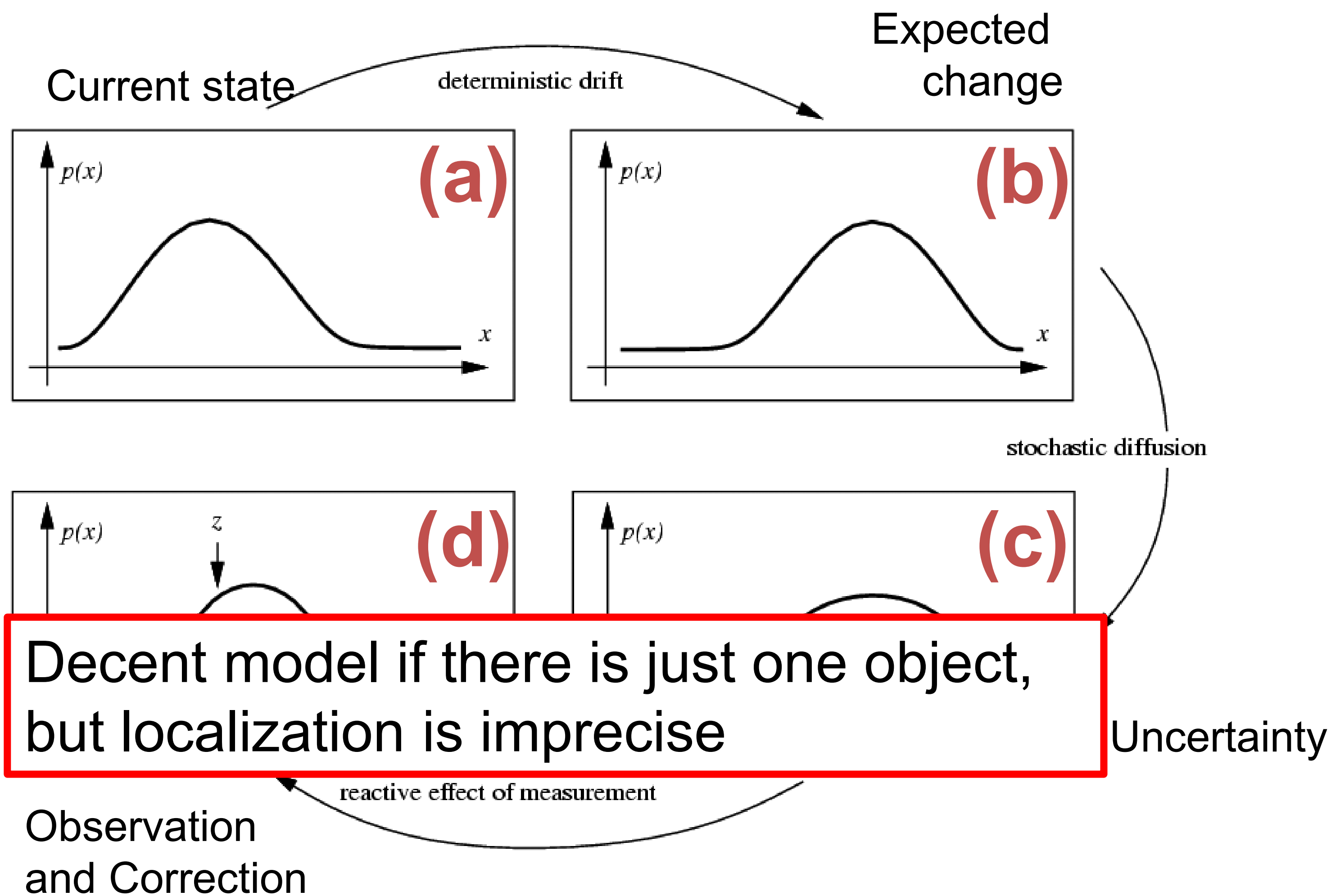
Propagation of Gaussian densities



Decent model if there is just one object, but localization is imprecise

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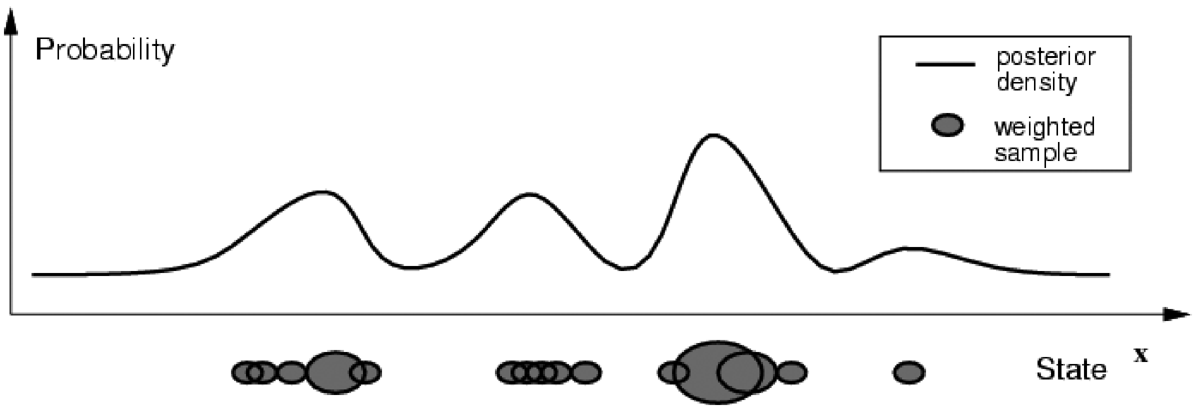
Particle filtering



Represent the state distribution non-parametrically

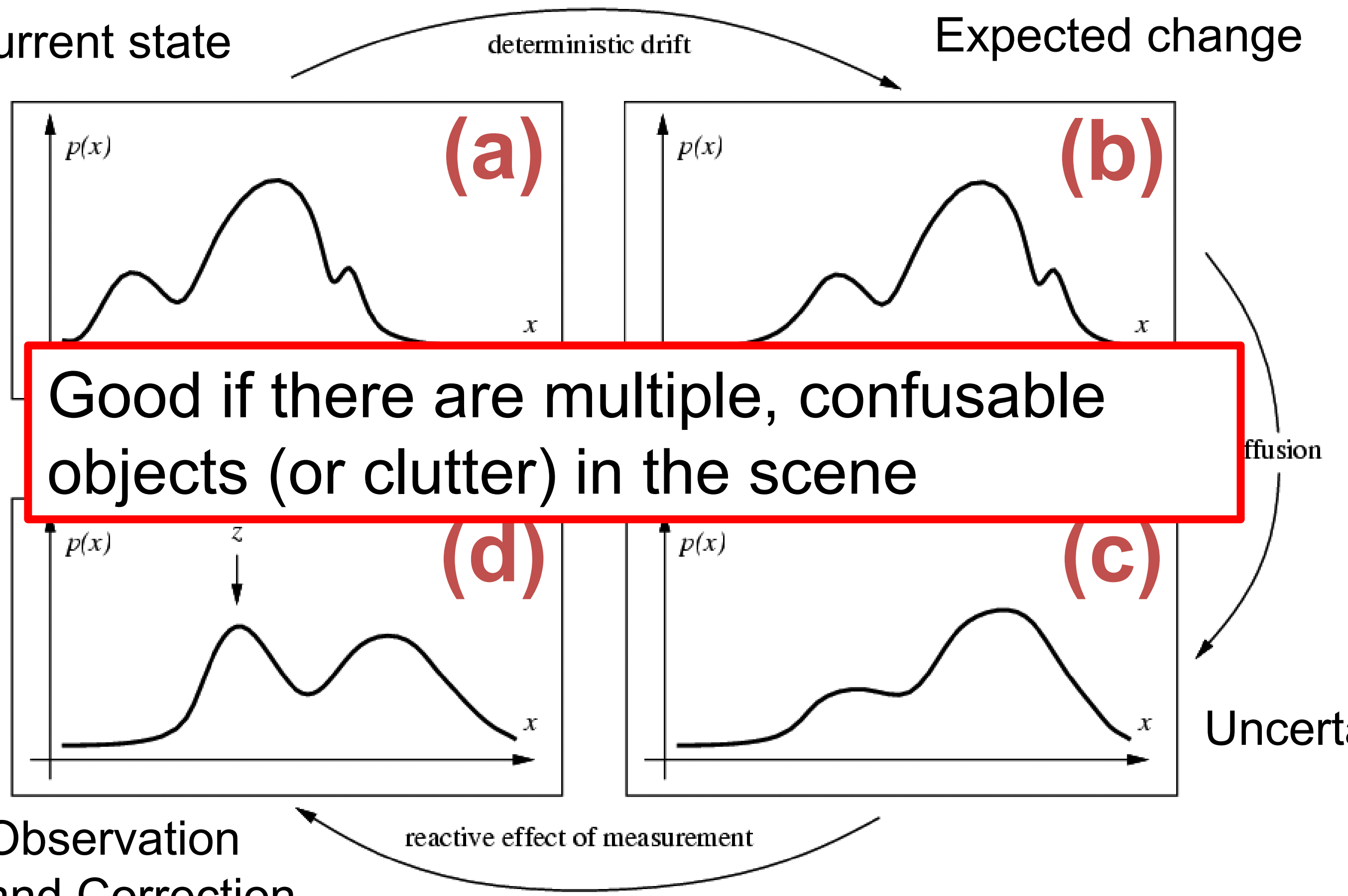
- Prediction: Sample possible values X_{t-1} for the previous state
- Correction: Compute likelihood of X_t based on weighted samples and $P(y_t|X_t)$

M. Isard and A. Blake, [CONDENSATION -- conditional density propagation for visual tracking](), IJCV 29(1):5-28, 1998

Non-parametric densities

Current state

Expected change



Good if there are multiple, confusable objects (or clutter) in the scene

Uncertainty

Observation and Correction

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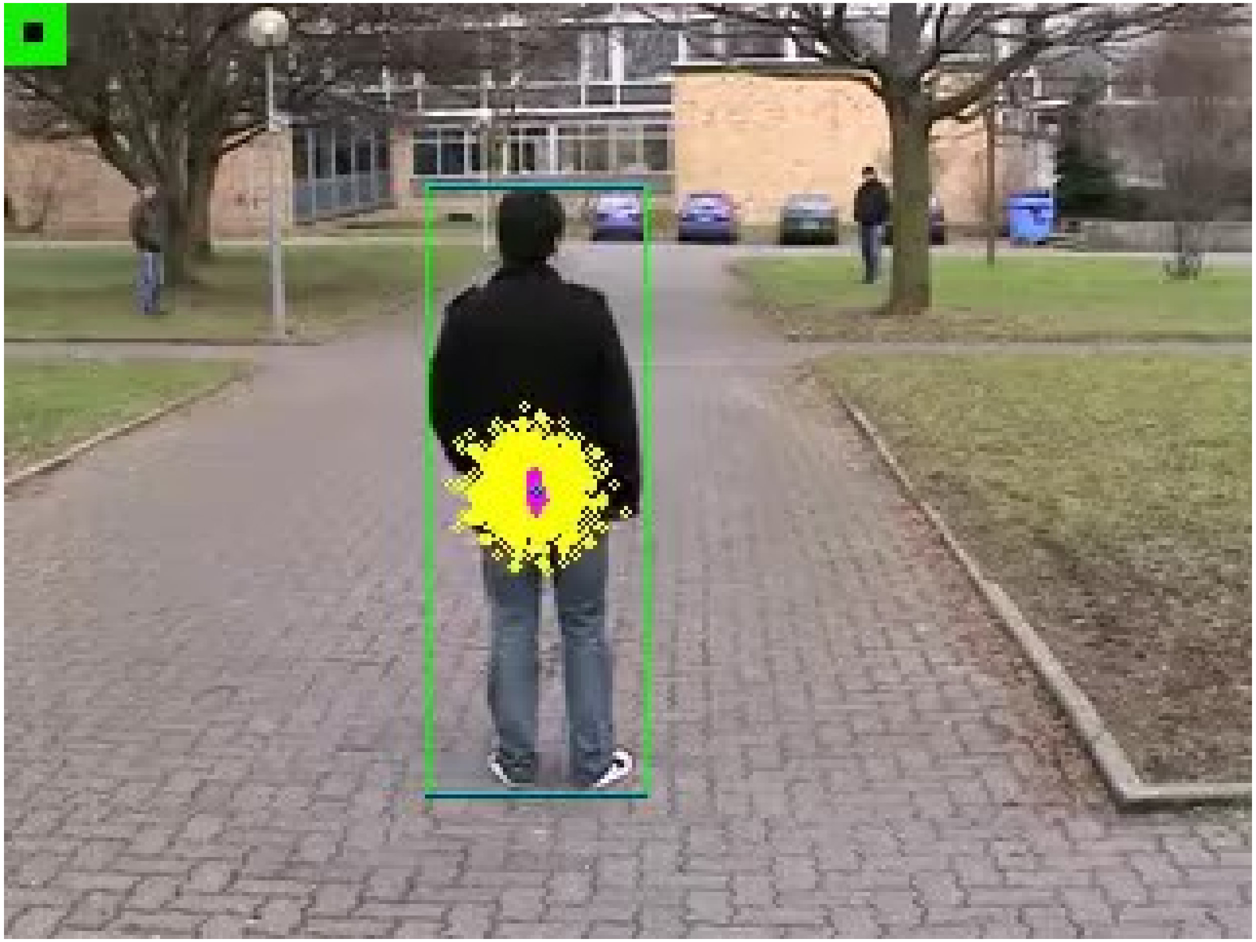
Particle Filtering

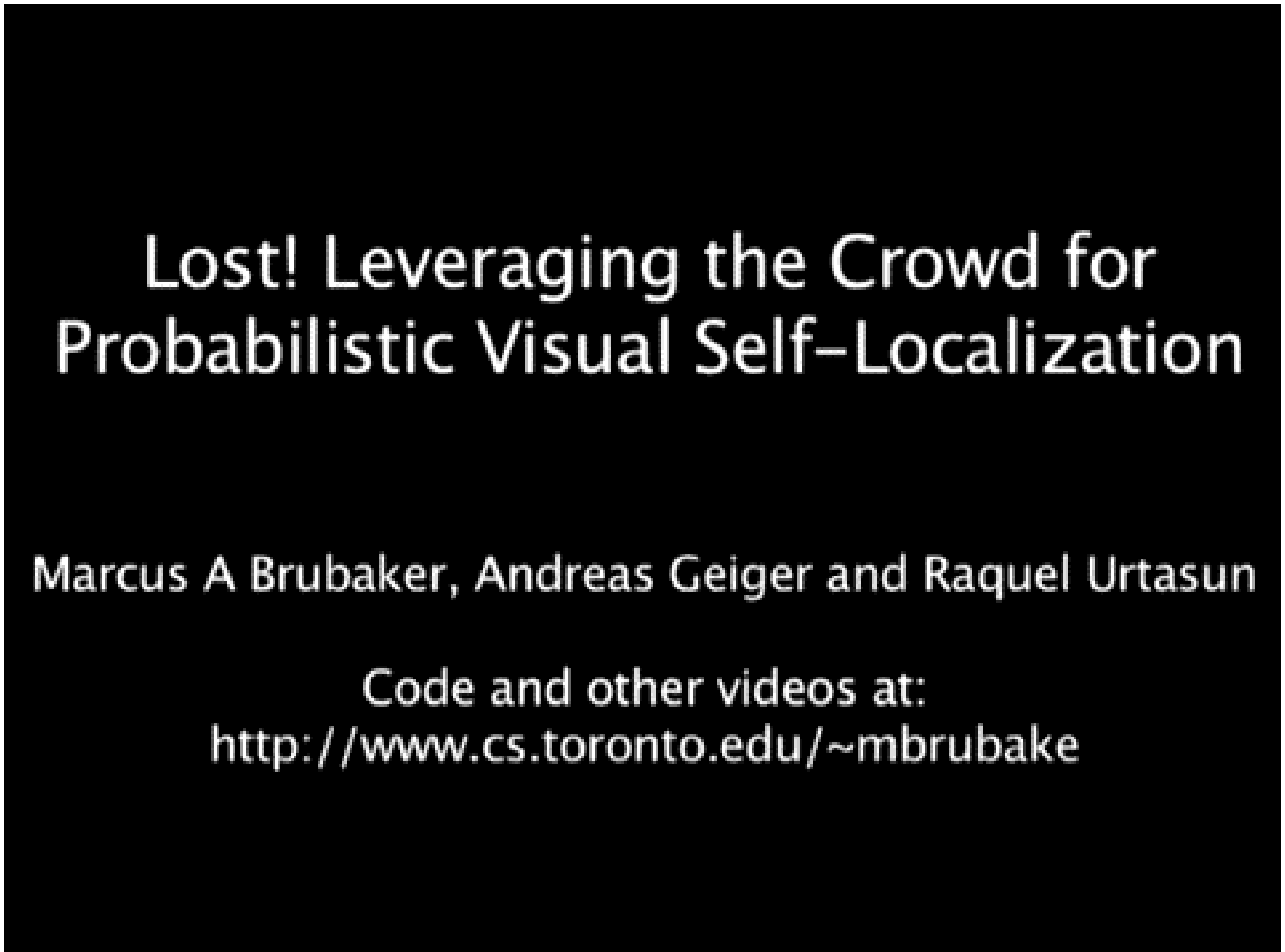


Particle Filtering More Generally

- Object tracking:
  - State: object location
  - Observation: detect bounding box
  - Transition: assume constant velocity, etc.

- Vehicle tracking:
  - State: car location [x,y,theta] + velocity
  - Observation: register location in map
  - Transition: assume constant velocity, etc.

Particle Filtering More Generally

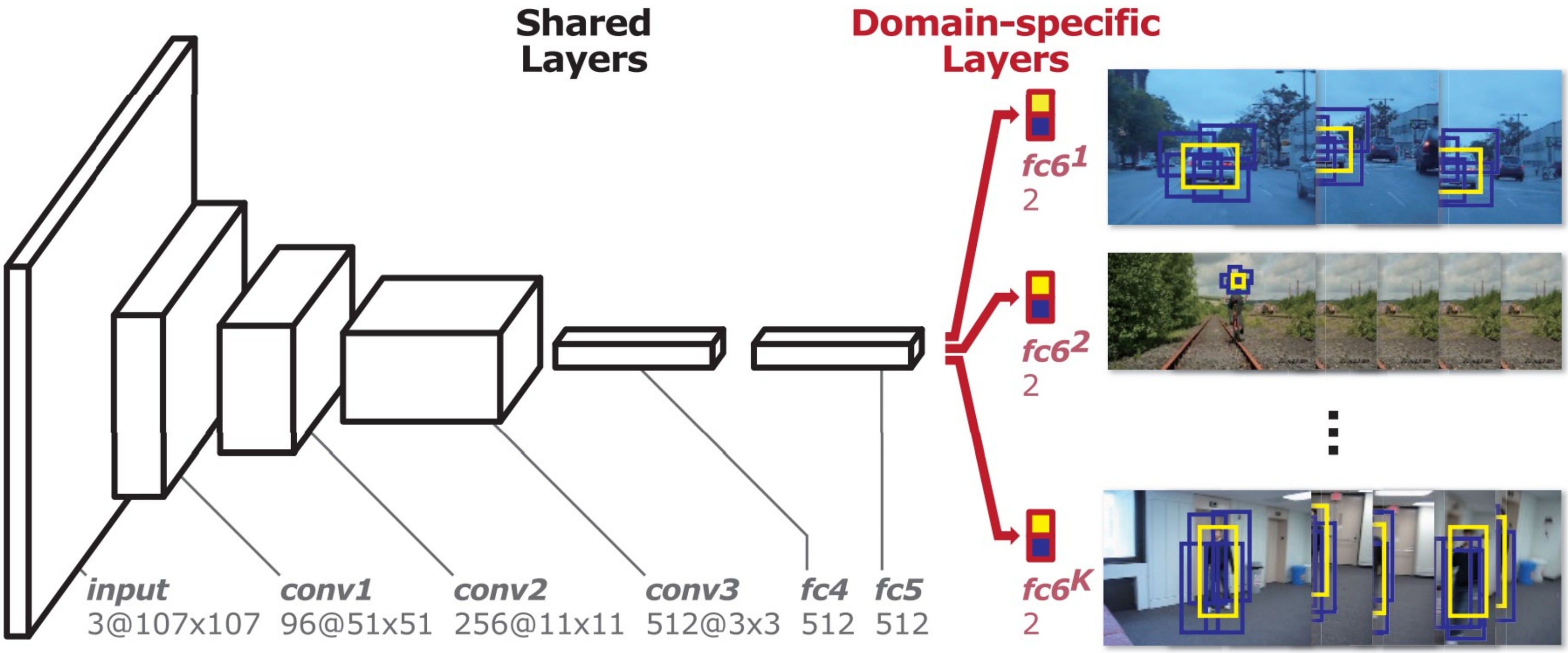


In General

- If you have something intractable:
- Option 1: Pretend you're dealing with Gaussians, everything is nice
- Option 2: Monte-carlo method, don't have to do intractable math

MD-Net

- Offline: train to differentiate between target and bg for K different targets
- Online: fine-tune network in new sequence



Nam and Han, CVPR 2016, Learning Multi-Domain Convolutional Neural Networks For Visual Tracking

Learning Multi-Domain Convolutional Neural Networks for Visual Tracking

Hyeonseob Nam and Bohyung Han

Nam and Han, CVPR 2016, Learning Multi-Domain Convolutional Neural Networks For Visual Tracking

Tracking Issues

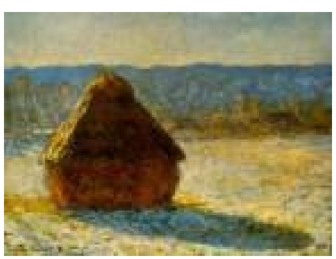
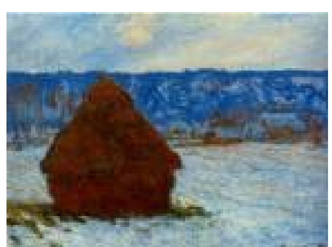
- Initialization
  - Manual (click on stuff)
  - Detection
  - Background subtraction

Slide credit: D. Hoiem

Detour: Background Subtraction

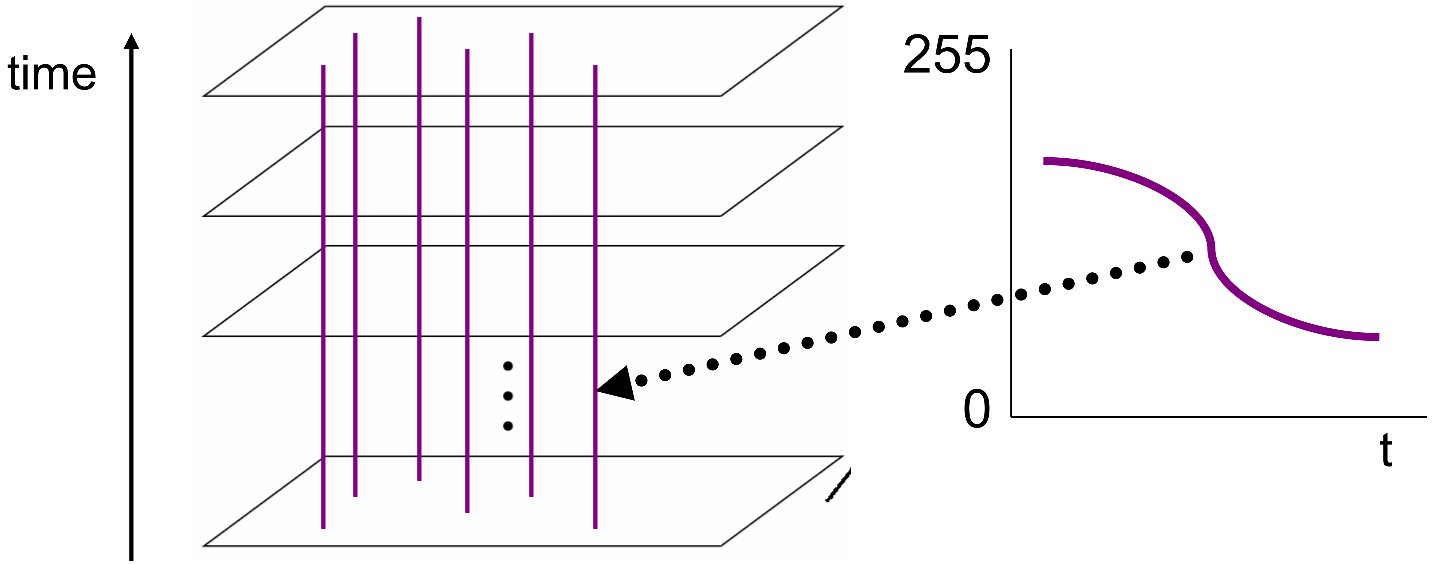
Moving in Time

- Moving only in time, while not moving in space, has many advantages
  - No need to find correspondences
  - Can look at how each ray changes over time
  - In science, always good to change just one variable at a time
- This approach has always interested artists (e.g. Monet)

Slide credit: A. Efros

Image Stack



- As can look at video data as a spatio-temporal volume
  - If camera is stationary, each line through time corresponds to a single ray in space
  - We can look at how each ray behaves
  - What are interesting things to ask?

Slide credit: A. Efros

Example

Slide credit: A. Efros

Examples

Average image

Median Image

Slide credit: A. Efros

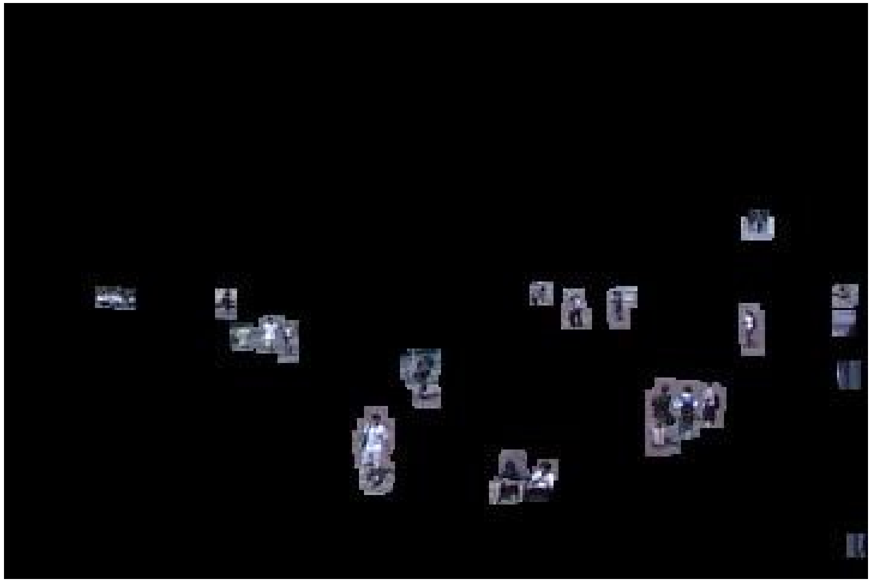
Average/Median Image

Slide credit: A. Efros

Background Subtraction

-

=



Slide credit: A. Efros

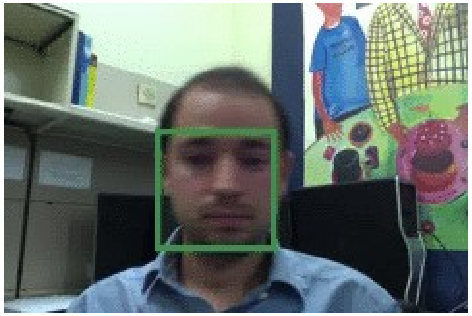
Tracking Issues

- Initialization
- Getting observation and dynamics models
  - Observation model: match template or use trained detector
  - Dynamics Model: specify with domain knowledge

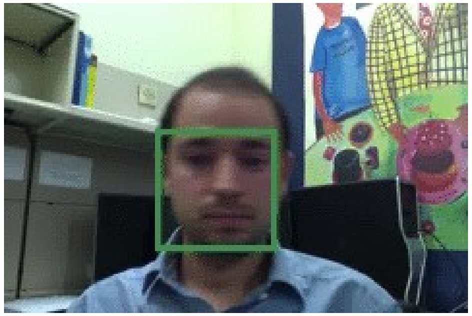
Slide credit: D. Hoiem

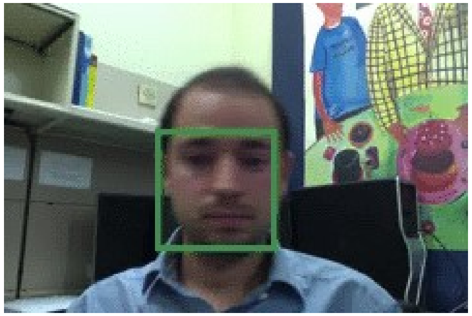
Tracking Issues

- Initialization
- Getting observation and dynamics models
- Combining prediction vs correction:
  - Dynamics too strong: ignores data
  - Observation too strong: tracking = detection



Too strong dynamics model





Too strong observation model

Slide credit: D. Hoiem

Tracking Issues

- Initialization
- Getting observation and dynamics models
- Combining prediction vs correction
- Data association:
  - Need to keep track of which object is which. Particle filters good for this

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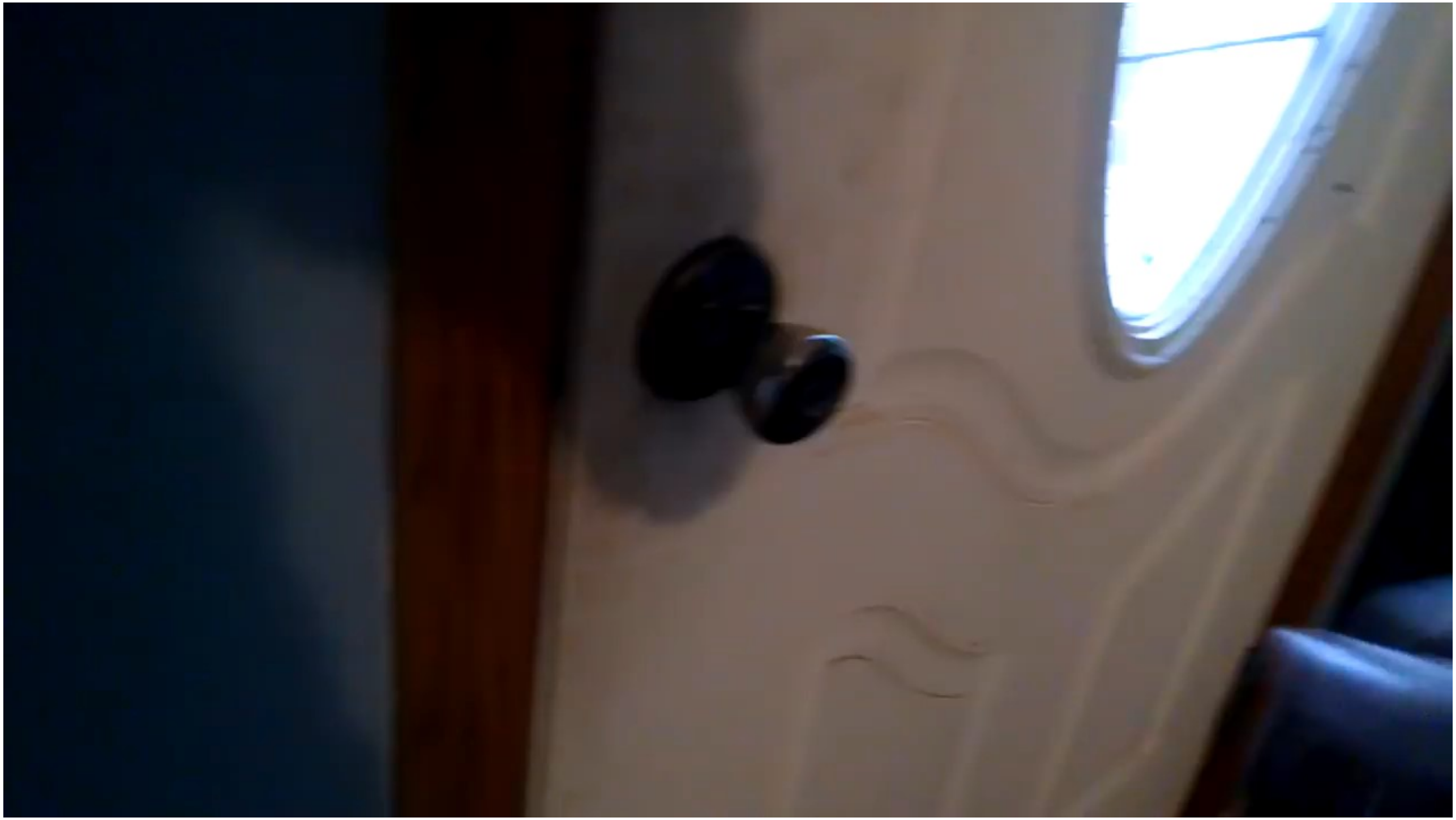
Tracking Issues – Data Association



Tracking Issues

- Initialization
- Getting observation and dynamics models
- Combining prediction vs correction
- Data association
- Drift
  - Errors can accumulate over time

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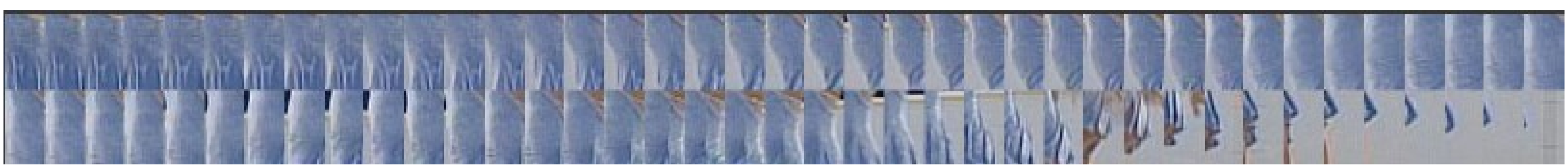
Drift



D. Ramanan, D. Forsyth, and A. Zisserman. [Tracking People by Learning their Appearance](). PAMI 2007.

Things to remember

- Tracking objects = detection + prediction

- Probabilistic framework
  - Predict next state
  - Update current state based on observation

- Two simple but effective methods
  - Kalman filters: Gaussian distribution
  - Particle filters: multimodal distribution

Slide credit: D. Hoiem

Action Recognition

- Image recognition:
  - Input: HxWx3 image
  - Output: F-dimensional output

- Action recognition
  - Input: ?x?x? video
  - Output: F-dimensional output

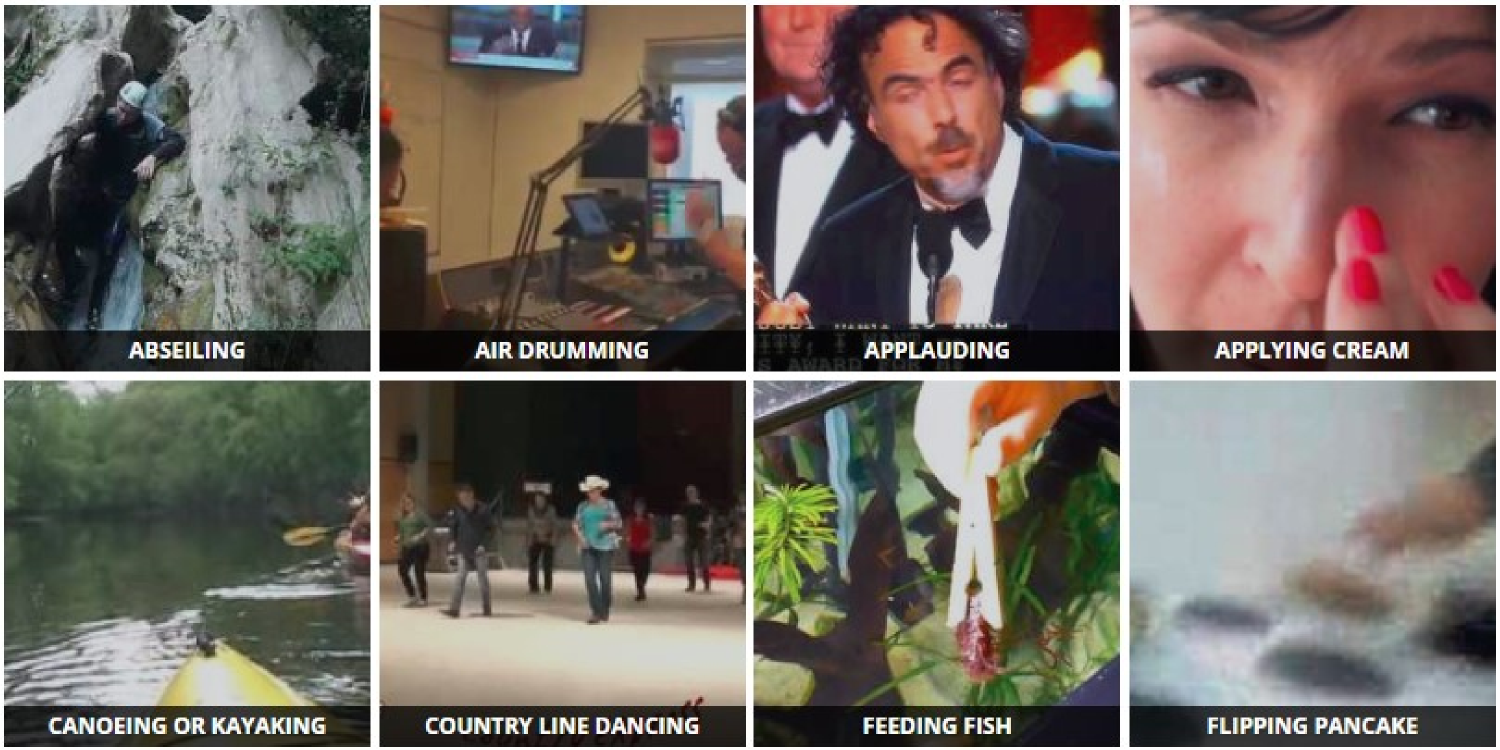
Datasets – KTH

#Classes: 6, Videos: 2391, Source: Lab, Year: 2004
Recognizing Human Actions: A Local SVM Approach
C. Schuldt, I. Laptev, B. Caputo

Datasets – UCF 101

#Classes: 101, #Videos: 9,511, Source: YouTube, Year: 2012
UCF101: A Dataset of 101 Human Action Classes From Videos in The Wild.
K. Soomro, A. Zamir, M. Shah

Datasets – Kinetics

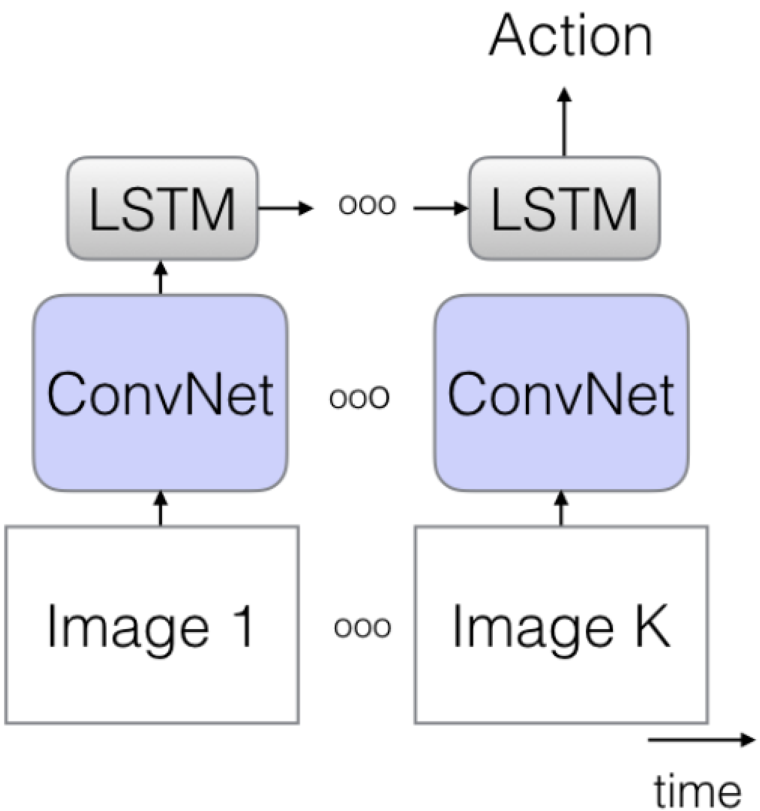


#Classes: 400, #Videos: 240K, Source: YouTube, Year: 2017

The Kinetics Human Action Video Dataset

W. Kay, J. Carreira, K. Simonyan, B. Zhang, C. Hillier, S. Vijayanarasimhan, F. Viola, T. Green, T. Back, P. Natsev, M. Suleyman, A. Zisserman,

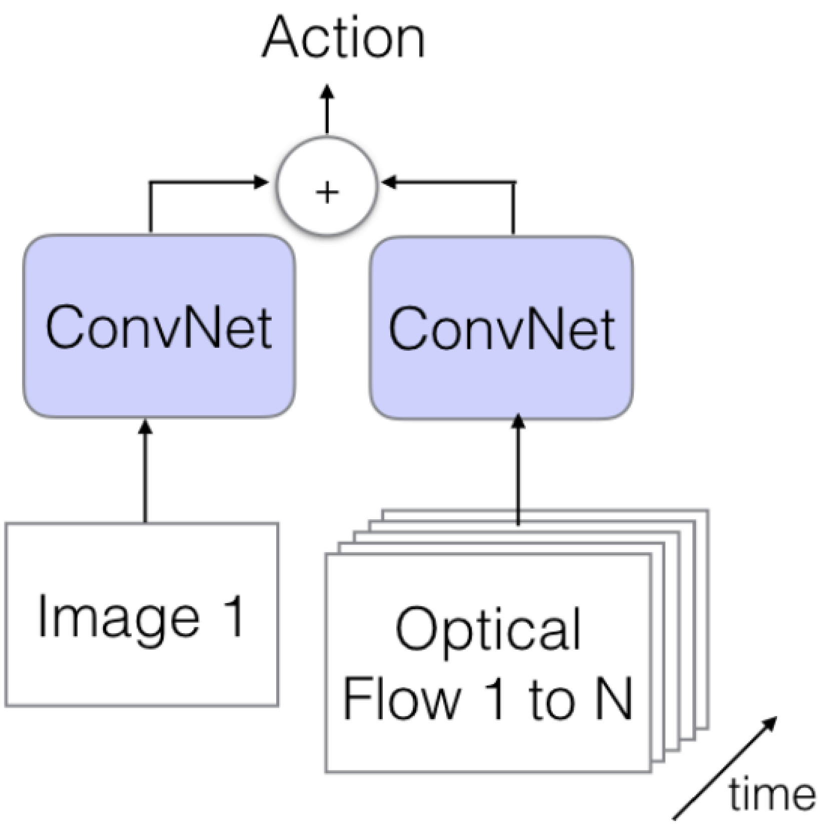
Models for Action Recognition



- Take learned sequence modeler (also used in language tasks, e.g., sentence -> sentiment)
- Feed in convnet activations as opposed to words

Diagram credit: J. Carreira, A. Zisserman

Models for Action Recognition



- One network (Image) takes HxWx3 image
- Other network (Flow) takes HxWx2*N image
- Add them together

Diagram credit: J. Carreira, A. Zisserman

Models for Action Recognition

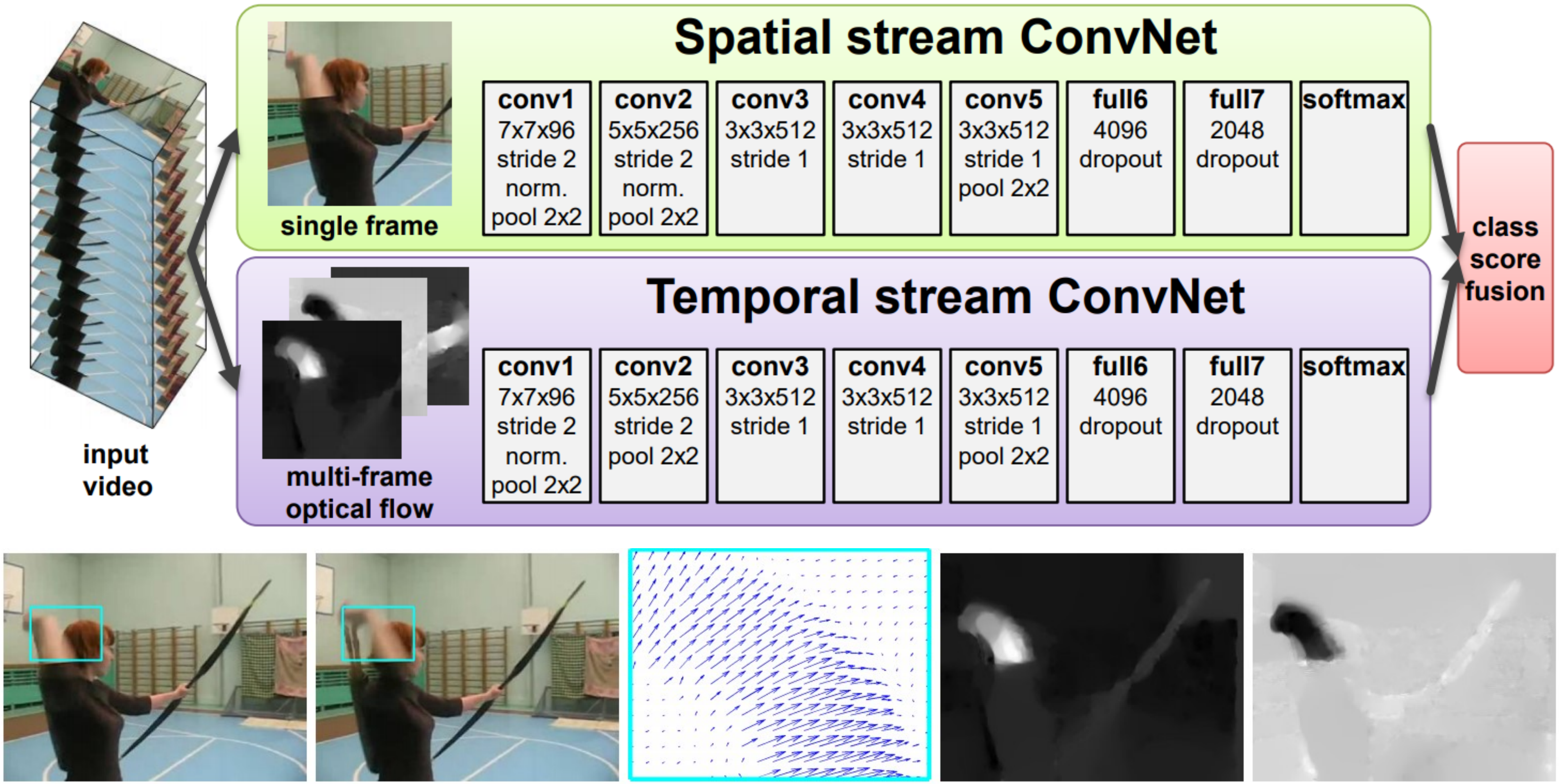
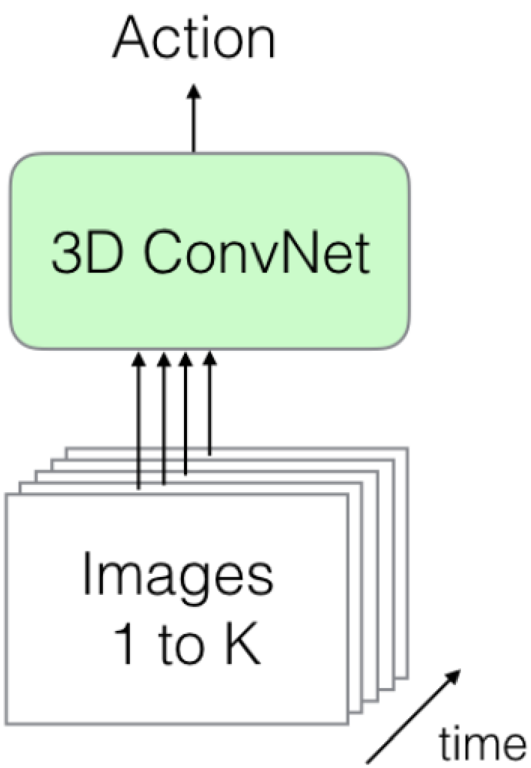


Diagram credit: J. Carreira, A. Zisserman

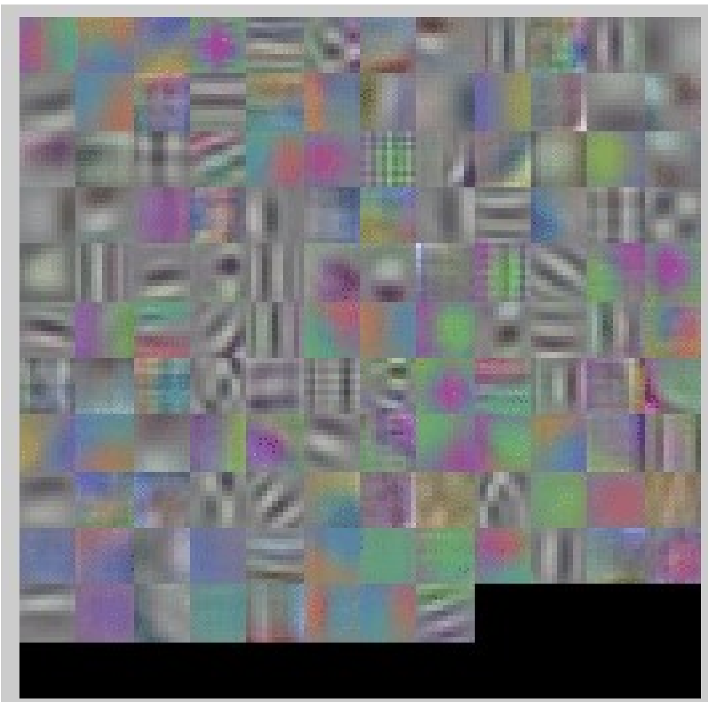
Models for Action Recognition



- Dump all the frames in as a HxWx3xN tensor
- Convolutions are 3D

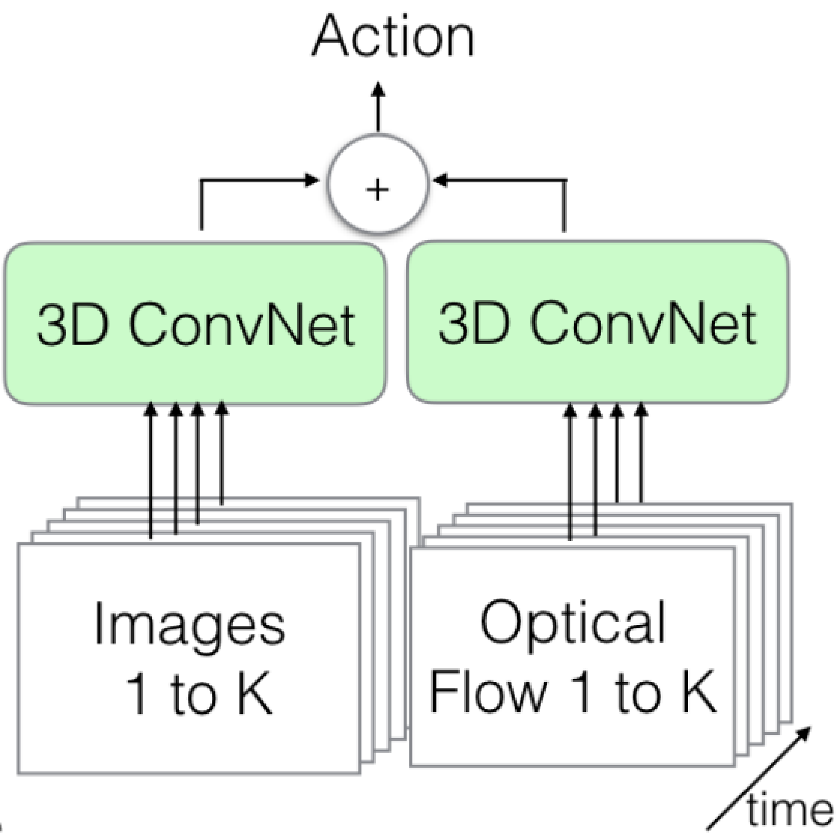
Diagram credit: J. Carreira, A. Zisserman

Models for Action Recognition



- Filters pick up on spatial patterns *and* motion patterns

Models for Action Recognition



- RGB frames go in as HxWx3xN tensor
- Flow frames in as HxWx2xN tensor
- Convolutions are 3D

Diagram credit: J. Carreira, A. Zisserman

Comparisons

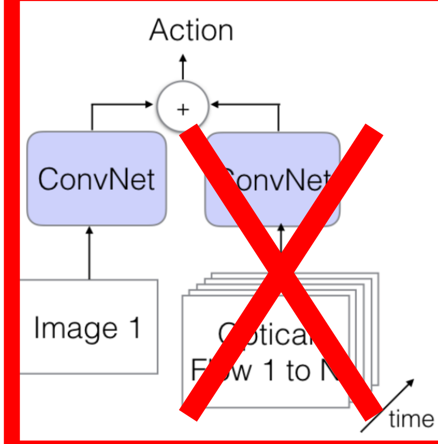
Take-homes:

- Flow + RGB does best
- 3D Convolutions does best

Architecture	UCF-101			miniKinetics		
	RGB	Flow	RGB + Flow	RGB	Flow	RGB + Flow
(a) LSTM	81.0	–	–	69.9	–	–
(b) 3D-ConvNet	51.6	–	–	60.0	–	–
(c) Two-Stream	83.6	85.6	91.2	70.1	58.4	72.9
(e) Two-Stream I3D	**84.5**	**90.6**	**93.4**	**74.1**	**69.6**	**78.7**

Hmm… #1

Just looking at independent frames does shockingly well.



Architecture	UCF-101 RGB	UCF-101 Flow	UCF-101 RGB + Flow	miniKinetics RGB	miniKinetics Flow	miniKinetics RGB + Flow
(a) LSTM	81.0	–	–	69.9	–	–
(b) 3D-ConvNet	51.6	–	–	60.0	–	–
(c) Two-Stream	$\boxed{83.6}$	85.6	91.2	$\boxed{70.1}$	58.4	72.9
(e) Two-Stream I3D	**84.5**	**90.6**	$\boxed{\textbf{93.4}}$	**74.1**	**69.6**	$\boxed{\textbf{78.7}}$

Hmm… #2

Using optical flow as input improves things. If flow is so important, can't it just learn this on its own?

Architecture	UCF-101			miniKinetics		
	RGB	Flow	RGB + Flow	RGB	Flow	RGB + Flow
(a) LSTM	81.0	–	–	69.9	–	–
(b) 3D-ConvNet	51.6	–	–	60.0	–	–
(c) Two-Stream	83.6	85.6	91.2	70.1	58.4	72.9
(e) Two-Stream I3D	**84.5**	**90.6**	**93.4**	**74.1**	**69.6**	**78.7**